Int. J. Production Economics 152 (2014) 200–209

Contents lists available at ScienceDirect

Int. J. Production Economics

journal homepage: www.elsevier.com/locate/ijpe

Mining logistics data to assure the quality in a sustainable food supply chain: A case in the red wine industry

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ARTICLE INFO

Article history:
Received 15 December 2012
Accepted 9 December 2013
Available online 24 December 2013

Keywords:
Quality sustainability
Supply chain quality
Wine industry
Association rule

ABSTRACT

In recent years, food supply chains have faced increased quality risk, caused by the extended global supply chain and increased consumer demands on quality and safety. Given the concern regarding quality sustainability in the food supply chain, much attention is being paid to continuous planning and monitoring of quality assurance practices in the supply chain network. In this research, we propose a supply chain quality sustainability decision support system (QSDSS), adopting association rule mining and Dempster's rule of combination techniques. The aim of QSDSS is to support managers in food manufacturing firms to define good logistics plans in order to maintain the quality and safety of food products. We conduct a case study of a Hong Kong red wine company in order to illustrate the applicability and effectiveness of QSDSS. Implications of the proposed approach are discussed, and suggestions for future work are outlined.

1. Introduction

Sustainability is one of the most important topics to emerge in recent years (Svensson, 2006; Linton et al., 2007). It encompasses the ideas of lean production and supply chain quality management that are now core to the strategy of most manufacturing firms. Moreover, the development of sustainability provides new ideas to reduce costs, since supply chain management considers the product from initial processing of raw materials to delivery to the customer (Linton et al., 2007). Thus, each operation in different supply chain tiers has the potential to be developed to reduce quality uncertainty, resource waste and operational cost, so minimizing waste.

Supply chain quality assurance represents a continual challenge to supply chain managers in food manufacturing firms. Most companies now include global sourcing as part of their procurement strategy, and the food supply chain usually crosses a number of borders to reach the end user. The severity and complexity of the product quality problem have been aggravated due to the magnitude of the global sourcing issue (Tse and Tan, 2011). Hence, there is a need for research in global food supply chain improvement (Kuo and Chen, 2010). If more members join the supply chain, more uncertainties accrue regarding the quality of the final food product. In such a complicated and multi-layered supply chain environment, firm executives may fail to anticipate the cascading effect that occurs routinely throughout their supply chain operations (Lamarre and Pergier, 2009). In the most serious case, the unsafe product may trigger a product recall that becomes a nightmare for the supply chain members. Another uncertainty factor that influences the effectiveness of product quality assurance is poor visibility in the supply chain (Roth et al., 2008). The dramatic increase in product recalls reveals that those multi-tiered supply chains with low transparency are particularly vulnerable to quality risk (Tse and Tan, 2012).

The intention of this paper is to propose a decision support framework that will reveal possible quality sustainability solutions in food supply chains. The framework will also provide a guide for managers on how to plan a logistics solution to assure the quality of food products in a distribution network. The paper develops a decision support model for supply chain quality sustainability (hereafter QSDSS) based on the association rule mining and Dempster's rule of combination. The RFID technology (Mo et al., 2009) is adopted in the proposed DSS to monitor and capture quality data, and association rule techniques are employed to data mine the good logistics plans used to transport food products in the distribution network, so as to reduce uncertainty and manage risk in the supply chain. In the proposed method, the first stage recognizes associations between logistics order flows (such as Factory A to Distributor B) and source to source relationships (such as mode of transportation, type of product, delivery period) by using association rule mining. In the second stage, an aggregation method is used to group interesting rules (discovered in association rule mining) for particular order flows with quality assurance settings by using Dempster's rule of combination. In order to test the validity of the proposed DSS, a case study is conducted with a Hong Kong red wine company, and its test results are evaluated by a focus group of academics and industrialists.

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0925-5273/$ - see front matter
http://dx.doi.org/10.1016/j.ijpe.2013.12.010

The remainder of this paper is organized as follows: Section 2 comprises a literature review. Section 3 describes the proposed QSDSS framework. Section 4 describes the case study of a Hong Kong red wine firm. Section 5 presents the discussion and managerial implications. Finally, in Section 6, conclusions are presented, along with summaries and guidelines for effective quality assurance in the red wine supply chain.

2. Related studies

2.1. Quality sustainability in the food supply chain

The food supply chain is defined as "the total supply process from agricultural production, harvest or slaughter, through primary production and/or manufacturing, to storage and distribution to retail sale or use in catering and by consumers" (Kuo and Chen, 2010).

Over the last decade, the increase in the number of food-borne pathogens and poisoning has altered the demands on and characteristics of the food supply chain (Lao et al., 2012; Henson et al., 1999; Unnevehr and Jensen, 1999). Quality assurance in the food supply chain is becoming more and more important, as it is necessary to satisfy customer needs that are directly related to social responsibility (Roth et al., 2008; Tse and Tan, 2012; Lao et al., 2012).

Food supply chain management requires caution and a strategic handling process, since improper handling practice can result in serious consequences, such as food poisoning and product recall. Therefore, the food supply chain requires a well-planned quality assurance practice in order to avoid the occurrence of quality risk (Tse and Tan, 2012; Tse et al., 2011). To control product quality to the fullest extent, it is necessary to ensure the proper quality sustainability of logistics operations in all supply chain entities. In a study of cold supply chain tracking, Montanari (2008) points out that the integrity of the food supply chain must be preserved from the point of production and processing, to storage at the consuming household or restaurant. Lao et al. (2012) argue that adoption of cautionary quality control in upstream supply chain members is imperative, particularly in the distribution centers. Van Der Vorst et al. (2009) state that in order to respond effectively to changes in quality and the environment, redesign of the entire food supply chain is vital. They further note that the design of the food supply chain has become complicated due to an intrinsic focus on product quality which is directly associated with integrity and safety. According to Svensson (2006), sustainable quality assurance practices should be adopted within a circulation approach, so as to create a chain and a series of business operations without loose ends.

Van Donselaar et al. (2006) and Van Der Vorst et al., (2009) argue that food supply chain sustainability is not limited to quality assurance, but also implies the reduction of food waste, whereby food products have to be disposed of because they have deteriorated. Kleijnen and Vorst (2005) state that the fundamental causes of waste in food supply chains are product quality deterioration and lack of supply chain coordination. In order to obtain quality sustainability, a redesign of supply chains and the adoption of tracking technology (such as RFID) are required. Montanari (2008) notes that each transport phase (e.g. loading, unloading, handling, and storage) in a food supply chain plays an important role in achieving the quality sustainability. Also, potential quality threats may result from the size of shipments, reliability of equipment, and ownership transfer of products moving through the transportation network. In addition, Kuo and Chen (2010), Hsu and Liu (2011) and Montanari (2008) stress the importance of temperature control of logistics movement and storage of food products in the cold supply chain for maintaining the original value and quality. Moreover, keeping track of the temperature conditions therein can identify the potential quality risk, the shelf life and final quality of chilled products.

2.2. Data mining association rule

Data mining is the process of finding the patterns, associations or relationships among data using various analytical techniques and involving the creation of a model, so that the concluded result will become useful information or knowledge. Association rule mining is one of the most popular data mining techniques in formulating decision support systems (Ting et al., 2012, 2010a; Chien and Chen, 2008; García et al., 2008). It aims to extract interesting correlations, frequent patterns, associations or causal structures among sets of items in databases (Kotsiantis and Kanellopoulos, 2006). A famous example of applying association rules is market basket analysis (Chen et al., 1996). Agrawal and Strikant (1994) introduce the Apriori algorithm for discovering regularities between products in large scale transaction data recorded by point-of-sale systems. The rules can be expressed as "$\{X, Y\} \rightarrow \{Z\}$ [support: 60% and confidence: 80%]" meaning that X, Y and Z occur in 60% of all transactions (i.e. support) and 80% of the transactions containing X and Y contain Z (i.e. confidence). In general, a rule is regarded as interesting if it satisfies the minimal thresholds for both support and confidence predefined by experienced users or domain experts.

Association rule mining is now widely adopted in decision support systems (DSS) in industrial and logistics applications. Ketikidis et al. (2008) develop an association rule DSS to provide decision support in material sourcing, production scheduling and physical distribution. Lau et al. (2009) develop a process mining DSS for identifying the root causes of quality problems in a supply chain, and for providing some configuration parameters to fine tune the operational process to improve the performance. Liao et al. (2008) propose an association rule DSS to develop product maps for new product development. Their DSS aim to investigate the relationships among customer demands, product characteristics, and transaction records in order to discover different knowledge patterns and rules from customers so as to develop new cosmetic products and possible marketing solutions. Tsai et al. (2009) adopt an association clustering technique to mine the correlated demands, and then to establish a joint replenishment policy, which significantly reduces the operational cost. Their proposed algorithm employs the "support concept" in association rule analysis to measure the similarity of different products. Hsieh and Huang (2010) propose a heuristics approach in order to provide an order picking system in a warehouse, where an association rule clustering analysis is used to find the highest relativity of different items in the same order picking batch. Similarly, Chen and Wu (2005) adopt an association rule clustering analysis to discover the associations between orders. The customer demand pattern is identified by discovering hidden rules, such as when the occurrence of some orders in a batch may also have the occurrence of other orders in the same batch.

There are a number of association rule DSSs aimed at streamlining integrated warehouse operations, such as order picking. There have been relatively few attempts at formulating a DSS for conducting data analysis from the upstream to downstream supply chain (Tse et al., 2009; Lau et al., 2009). However, operations in different supply chain members are closely related to each other, and tiny changes in each operation may generate a significant difference in the other mined rules (Kim, 2007). Thus, if one concentrates attention on only one particular supply chain tier, he may fail to obtain the effective association rules in the entire distribution network, since the attributes of the associate rule also interact with elements in other supply chain tiers. In this research, we propose a logistics solution mining system with an iterative mining algorithm embedded for supporting logistics and quality solution discovery in a food supply chain. As stated in Foster (2008), the information ascertained from data mining can be used to improve supply chain quality sustainability. Data mining has turned out to be important for ensuring a certain level of quality within transportation logistics, particularly important in the food supply chain as it is highly dependent on the in-transit conditions, such as temperature, degree of light exposure, shock/vibration level, and humidity.

In this study, the decision support model for supply chain quality sustainability (QSDSS) is evaluated in an Italian-based red wine company in Hong Kong to show how it can find the relationships among logistics parameters, environmental parameters and the presence of quality problems. A red wine company is selected in this case as red wine is a fragile product, sensitive to environmental change. For example, many wine collections have been damaged during transit because of instability in temperature. High temperatures (higher than 65 °F or 18 °C) can cause wine to age prematurely, thus losing its flavor and balance; when the wine is overly chilled, it also loses its flavor and aromas (BetterTastingWine, 2006). Moreover, vibration and fluctuation in humidity may also lead to negative effects in wine quality (Chung et al., 2008). Therefore, the red wine company and its logistics providers strive to find ways to design better transport routes in order to provide a transit environment in which the red wines can be transported with limited changes in their physico-chemical properties.

3. QSDSS: mining logistics order flows and source to source relationships

In terms of supply chain quality sustainability, association rule mining is employed to discover the association measures (support and confidence) between logistics order flows (such as Factory A to Distributor B) and source to source relationships (such as mode of transportation, type of product, delivery period) from the transportation logistics database. The database records all the logistics related data between each delivery; for example, Product X (product type) is shipped on 8 December 2011 (event date) at 05:00 (event time) from Factory B (shipping location) to Factory C (destination). Fig. 1 depicts a logistics flow scenario with type of data (to be) recorded. By discovering these flows with association rule mining, quality assurance settings for particular transportation logistics (or route) can be specified and highlighted.

Fig. 2 shows the decision support model for supply chain quality sustainability (QSDSS). QSDSS starts from the point where the logistics operator interprets the product type and quantity to be shipped, as well as the logistics flow (or route). As shown in Fig. 2, a new case (product type, quantity, route and mode of transportation) is first codified and processed by comparing with the previous records (or cases) retained in the knowledge base. To improve the decision analysis in data mining, all the 2 (or above)-level logistics flows (e.g. A–B–C, A–D–C–E, etc.) are segmented into 1-level flows; for example, if the flow is A–B–C, then it is separated into 2 flows, i.e. A–B and B–C. Then, data cleaning and pre-processing are conducted to select attributes or features which are useful for decision support in quality assurance settings.

3.1. First stage: discovering interesting rules

In the present study, association rules mining is used to extract the most interesting association rules based on support and confidence measures. A standard association rule consisting of an antecedent (i.e. X) and consequent (i.e. Y) is implied as follows:

$$X \Rightarrow Y \text{ where } X, Y \subset I \text{ is an itemset} \tag{1}$$

where X is the set of problem features of the new case, and Y is the suggested quality assurance settings (e.g. the product should be shipped by air-cargo within a temperature range of 5–60 °C).

The interestingness of a rule is measured by its support (i.e. the probability that the antecedent and consequent occur among cases in the knowledge base) and its confidence (i.e. the conditional probability that the consequent occurs given the occurrence of the antecedent). Support and confidence are taken jointly as measures of association between any pair of itemsets. We adopt the support–confidence measurement approach in the QSDSS, as it is a popular and appropriate approach to define rules, and is widely adopted in different data mining systems in various industries (Karpinets et al., 2012; Ting et al., 2010b; García et al., 2009; Shim et al., 2012; Sangelkar et al., 2012). Moreover, Dasseni et al. (2001) claim that the support–confidence measurement framework is a strong approach for the discovery of frequent itemsets, as interesting rules are the ones where both the support and the confidence are high.

Support and confidence are determined by the following equations, respectively:

$$\text{Support}(X \Rightarrow Y) = \frac{\text{Number of cases containing both } X \text{ and } Y}{\text{Total number of cases}} \tag{2}$$

$$\text{Confidence}(X \Rightarrow Y) = \frac{\text{Number of cases containing both } X \text{ and } Y}{\text{Number of cases containing } X} \tag{3}$$

The algorithm of association rules mining is shown in Fig. 3. The Apriori algorithm (Agrawal and Strikant, 1994), the best-known algorithm to mine association rules, is applied to identify the associations. It uses a breadth-first search strategy to count the support of rules, and a candidate generation function which exploits

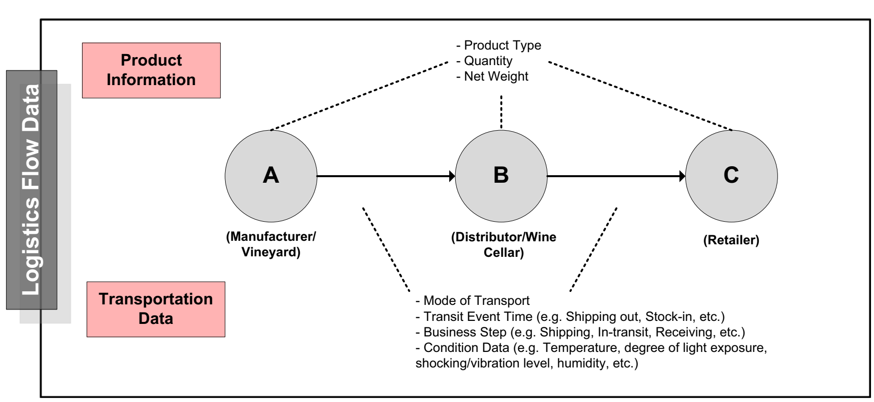

Fig. 1. Logistics flow scenario with type of data (to be) recorded.

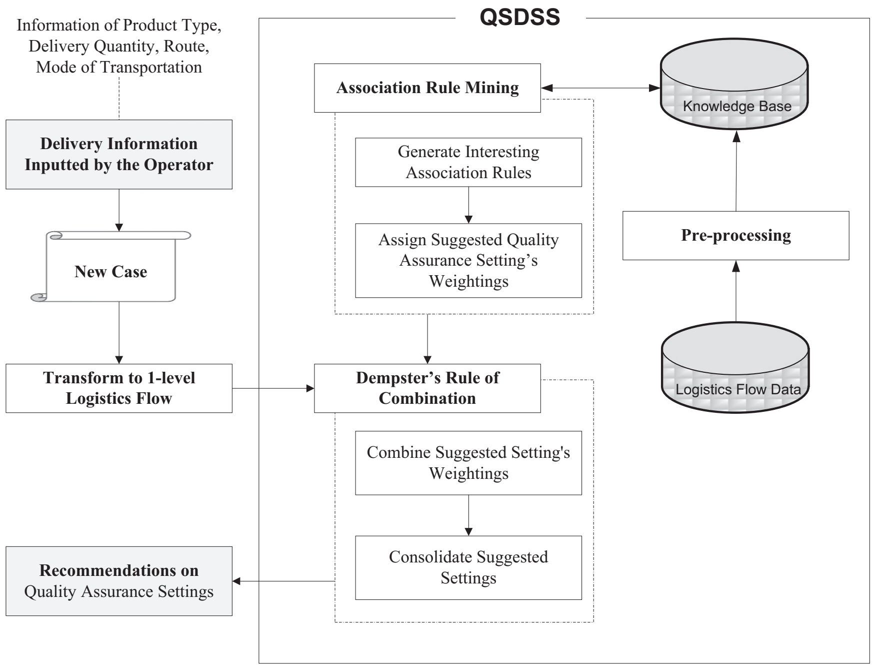

Fig. 2. Architecture of Decision Support Model for Supply Chain Quality Sustainability (QSDSS).

Input: Logistics information determined by the operator
Output: A set of quality assurance settings in a ranking list

Preprocessing
Set the minimal support α and minimal confidence β

Association rules mining algorithm
Do while (a new case is ready)
  Trigger Apriori algorithm
    Measure the support of the features of the new case
    Remove the features that do not satisfy α
    Measure the support of the settings
    Remove the settings that do not satisfy α
    Trigger Rule Extraction
      Associate filtered settings with the filtered features
      Measure the support and confidence of the association rules
      Remove the rules that do not satisfy α and β
    End Trigger
  End Trigger
  Extract the list of quality assurance settings from the associated rules
  Trigger Weighting Assignment
    Compute the weights for each assurance setting in the list of quality assurance settings
  End Trigger
  Sort the list of quality assurance settings by their weights in descending order
End Do
Report the results

Fig. 3. Algorithm of association rules mining in QSDSS.

the downward closure property of support. The algorithm is applied in the present study to speed up the mining process. Then, the mined rules are consolidated to extract a list of quality assurance settings.

Once the mined rules are generated, all consequents (or quality assurance settings) are individualized and assigned a weight. The weightings of the quality assurance settings in the list are determined by the maximum confidence of the rules associated with the corresponding settings, as shown in the following equation:

$$W_j^{arm} = \text{Max}\,\{Confid(a_1 \Rightarrow d_j), Confid(a_2 \Rightarrow d_j), \ldots, Confid(a_m \Rightarrow d_j)\} \tag{4}$$

where W_j^{arm} is the weighting of a setting j, a_i is the i-th problem feature, d_j is the j-th setting, and m is the number of problem features.

3.2. Second stage: aggregating interesting rules

The associations between logistics flow order and source to source relationships obtained in the first stage are used as the basis for aggregating the quality assurance settings. Considering a complete logistics route, it is important to merge the suggested settings of each 1-level logistics flow into a single one. Taking the above mentioned example (i.e. A–B and B–C) again, an aggregation method is used to group settings of the flow "A–B" and "B–C" back to a single flow, i.e. A–B–C. In order to combine the results and avoid duplication of the settings, Dempster's (1968) rule of combination is adopted. As the number of suggested settings in each flow is different, it is necessary to normalize the weightings of the suggestions by the following equation:

$$N_j = \frac{W_j}{\sum_{i=1}^{n} W_i} \tag{5}$$

where N_j and W_j are the normalized weighting and suggested weighting of setting j of first logistics flow (or second logistics flow), respectively, and n is the number of settings in the suggested list of settings of first logistics flow (or second logistics flow).

Supporting various logistics flows for a particular case, the mechanism of Dempster's aggregation approach offers the possibility to investigate the most appropriate path. To simplify the logic an example, as shown in Fig. 4, depicts the algorithm of combining the suggestions of first logistics flow with those of second logistics flow. A simple rule of combination is proposed to integrate the normalized weightings of first flow and second flow into one single solution. The combination method is adapted from Dempster's (1968) rule of combination, which compensates for the missing settings in the solutions of first flow or second flow, and updates the weightings of the settings when new evidence is available. The combination weights of the settings are calculated from the aggregation of normalized weightings of first flow and second flow as shown in the following equation:

$$N_i^{com} = \frac{w_i^{1st} N_i^{1st} + w_i^{2nd} N_i^{2nd}}{w_i^{1st} + w_i^{2nd}} \tag{6}$$

where N_i^{com}, N_i^{1st}, and N_i^{2nd} are the combined weighting of setting i, normalized weighting of first logistics flow of setting j, and normalized weighting of second flow of setting i, respectively, and w_i^{1st} and w_i^{2nd} are weighting of second and first logistics flow

Input: A set of settings in a ranking list from first and second logistics flow
Output: A set of quality assurance settings in a ranking list

Preprocessing
Set the threshold γ as the maximum number of settings of the output settings list

Suggestions combination algorithm
Do while (the input is ready)
Normalize the weighting of settings list of first logistics flow
Normalize the weighting of settings list of second logistics flow
Combine the weighting of settings lists of first and second logistics flow
Sort the unique settings list by their weights in descending order
Extract the first γ settings
End Do
Report the results

Fig. 4. Algorithm of suggestion combination in QSDSS.

for combination of setting *i*. The final solution is then sorted by the combined weightings of the setting in descending order.

As a result of the above process, the logistics flow order and source to source relationships can be identified. The association rule mining may suggest a formal rule with weights such as "If 8 pieces of Product X are to be shipped from Factory B to Distributor B via sea transport, then transit should be under the conditions: (i) temperature under -10 °C (with weight 0.75), (ii) vibration degree under 20 Gal (with weight 0.68), and (iii) delivery time within 2 days (with weight 0.79)." Thus, the association rules can be employed to design and identify the in-transit conditions by adequately grouping settings for particular routes, in which they have relatively high associations with each other. Therefore, the quality level of the transported product can be guaranteed and assured.

4. Case study

A case study has been conducted in collaboration with Collazoni (pseudonym), a famous Italian vineyard and wine producer. There are five wine cellars located in Hong Kong for importing and distributing the wine products to the Europe and Asia regions. To enhance the quality assurance during transportation, Collazoni adopts Radio Frequency Identification (RFID) to uniquely identify and prevent counterfeiting of each wine product, and cold chain technology to monitor temperature (Kwok et al., 2010b, 2010a). As a result, Collazoni can monitor the temperature condition in the transit period and track the bottles from the point at which they are shipped from the wine producer until they leave the local importer, en route to the wine shop.

4.1. Quality assurance challenges in Collazoni

As reported by Savage (2012), 88% of collectors pay more for wine with good provenance (i.e. proof of a wine's storage history). Therefore, as a leading wine producer and distributor, Collazoni has to ensure that it meets market demand in terms of quality assurance in order to keep pace with the competition. Since 2010, Collazoni has been shipping its wine products direct from vinery to the global market through its own Hong Kong based wine cellars. However, the firm has encountered cold chain breaks in the wine distribution, whereby for most of the time the wine products are refrigerated incorrectly via road transport (i.e. not in the range 10–16 °C). As a result, the wine will age prematurely, thus losing its flavor and balance as well as price premium.

Despite the adoption of RFID and cold chain technology, the need to distribute the wine products around the world means that it is difficult for Collazoni to monitor the temperature at each intermediate point in the supply chain. To avoid any temperature instability existing in these intermediate points, Collazoni needs to design better quality assurance settings for wine distribution. However, such approaches are difficult to achieve, as the logistics data are both complex and uncertain in nature, thus making it hard for the operator to determine the best settings. Owing to the potential quality hazard (as the wine can lose its flavor and balance) and the lack of recommendation in quality assurance settings, Collazoni was selected as the reference case to demonstrate the feasibility of the QSDSS.

4.2. RFID and cold chain deployment

In the case study, passive Impinj White Wet Inlay RFID tags and CSL CS203 Integrated RFID readers were used to create the RFID environment for capturing information on logistics flow and temperature monitoring. An RFID tag was affixed to the bottle of each wine product, as shown in Fig. 5a. Furthermore, the box was sealed with a battery-assisted cold chain tag (i.e. the green tag as shown in Fig. 5b) to monitor the temperature of the box (or wine) during the in-transit process. With the wireless communication capability of the cold chain tag, the operator can monitor the real-time temperature condition via a web-based system.

The RFID reader is able to simultaneously record 500 tags with an average reading time of 1 s. It can correctly read tags with an accuracy of 100% when there are fewer than 100 tags scanned at one time. The RFID environment was designed to allow 100 boxes to be put onto a large pallet during shipping and delivery to other parties. The results of the tests indicate that there is about 1% error rate due to reading conflict, and two readings were required to detect all the tags correctly.

4.3. Applying QSDSS to Collazoni's supply chain

To demonstrate the feasibility and practicability of the proposed decision support model for supply chain quality sustainability, the QSDSS was implemented in Collazoni. Fig. 6 depicts the conceptual framework of the information flow between the proposed supply chain network and the stakeholders. Each wine product is first tagged by RFID at the vineyard, thereby providing detailed information on the product. Every party in the supply chain network (i.e. from vineyard to distributor) is equipped with RFID readers to register the point-to-point transactions and temperature information of the products. With its automatic feature for data acquisition, the entire process of the provision of information visibility becomes more efficient. As a result, Collazoni's operator is able to input the logistics information (i.e. mode of transportation, type of product, delivery flow/route and period) into the QSDSS to analyze the quality assurance settings in the particular logistics flow.

4.3.1. Stage 1: rules discovery

In this case study, 10 factors are inputted for association rule mining. As shown in Fig. 3, a threshold support and confidence are predefined for each factor; in this case all threshold values are decided by the experienced operators in Collazoni (Zhang et al., 2004). In this study the threshold values of both support and confidence for all interesting rules are set as 0.6. If the support count of any item is smaller than the minimal threshold predefined, the corresponding item will be pruned. Take "Temperature = 30 °C" under the route "A–B" as an example: since the support count is 0.86, and the threshold value is set as 0.6, "Temperature = 30 °C" will remain and will not be pruned. However, since the support count for the factor "Event Time = 05:00", as its support count is smaller than that of threshold value 0.6, it will be pruned. Then, the candidates from the 1-itemset table are entered for the combination of the

Fig. 5. (a) RFID tag and (b) battery-assisted cold chain tag adopted in the case study.

2-itemset. All possible outcomes can be generated by concentrating their factors. After forming the 2-itemset, calculation of its support count is conducted. Similar to the previous steps, all the support counts are compared with the threshold values. The algorithm continues to establish the itemset tables and search for rules only if a 2-itemset table is formed. The algorithm may come to an end if the 2-itemset table does not contain any feasible combination. Where there are still feasible solutions, work has to be continued. To objectively extract the useful and interesting rules with certain support, Eq. (3) is employed for determining the confidence value of the remaining itemset. In total, 145 rules are generated for the route "A–B", of which Table 1 shows the first 10 interesting rules generated by association rule mining.

4.3.2. Stage 2: rules aggregation

In this stage, the qualified rules are passed to the aggregation algorithm, as shown in Fig. 4, for further determination of quality assurance settings when all the rules (within a completed logistics flow) are considered. Take the route "A–B–C" as an example: Table 2 shows all the normalized weightings of factors in the routes "A–B" and "B–C". By using Eq. (6), the factors of these two routes are combined and calculated as a single solution, i.e. the unique list of quality assurance settings. The final aggregation result of the factor "Season = Winter" is 0.65.

After the rules aggregation process, all the weighted settings can be ranked in descending order by value. So for example, the operators can consider "SHIP 90 bottles of 82′ Lafee wine" in the specific logistics route. Under such settings, the quality level of wine can be guaranteed.

Moreover, QSDSS facilitates continuous learning, as each logistics order is inputted into the system. This is because each new case inputted is stored, along with its quality result, and can be evaluated by the experienced operators in Collazoni. If the result is satisfactory, the new case with solution is validated and will be stored in the knowledge base for association rule mining. In other words, it is used as the actual learning process for facilitating analysis of assurance settings for each new case.

5. Performance evaluation and discussion

In order to evaluate the performance of QSDSS, a focus group was formed, comprising two senior managers, a project consultant and a logistics coordinator. These four members did not have prior knowledge about the development and implementation of QSDSS, thus they were able to give an independent evaluation. After a 12-month period, the focus group found the results encouraging and believed that the QSDSS system could enhance the quality assurance during transporting of the wine products. One of the managers commented that the QSDSS could fully utilize the RFID systems which were already being applied in the facilities (i.e. vineyard, distributor and retailer) in 2010. He also pointed out that the knowledge of quality assurance can be achieved/mined from the previous massive raw data stored in the data warehouse. Moreover, all the new case information will be inputted into the knowledge base and allow a continuous and iterative process to mine for solutions to future problems. Another manager claimed, "*…the new discovery and reuse of knowledge in logistics are our new competitive advantage…. The solution planning support of QSDSS can ensure our expensive products are kept in good condition during the transit stage.*" However, the logistics coordinator noted that some of the suggested settings might increase the cost of transportation. For example, the new solution suggested separating two different red wine products into two logistics flows. Nevertheless, both managers stated that they should not trade-off between quality and logistics cost: "*This is not a problem to split the order… We should put the quality as the first priority, since the loss of product return [note: due to quality problem in transit] or of spoiling the whole batch of wines is much more expensive than the cost of an extra-shipment.*" Overall, the focus group members were very pleased with the insight gained from QSDSS, and they further suggested extending the tracking functions by capturing the parameters of humidity and shock level in transit between Collazoni′s facilities.

In summary, QSDSS enhanced the supply chain quality sustainability performance of Collazoni in four categories: quality level enhancement, inspection cost reduction, customer satisfaction,

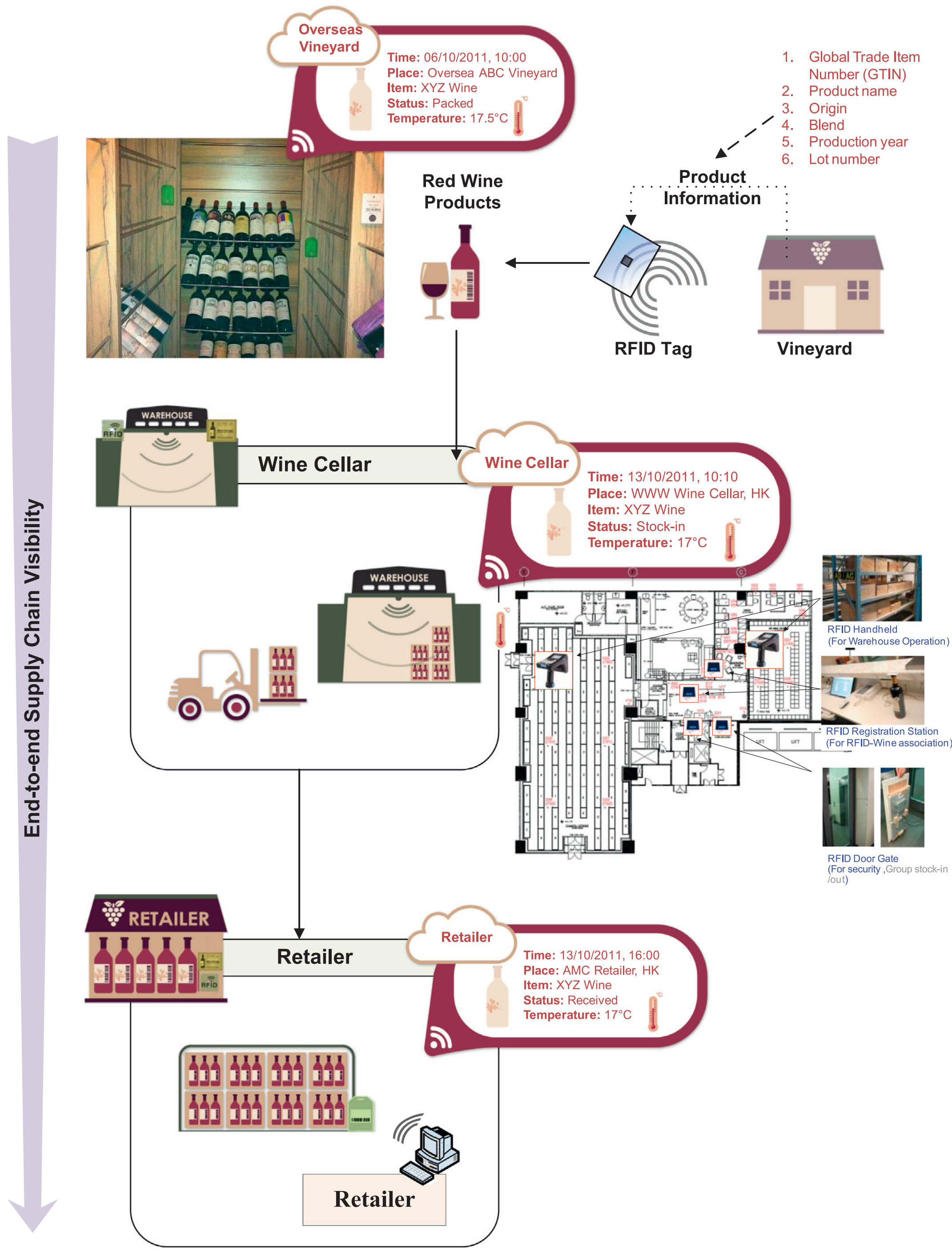

Fig. 6. Conceptual framework of the information flows between the proposed supply chain network and stakeholders.

and supply chain visibility improvement. Some of these have been verified by the case study.

5.1. *Improvement of quality level*

In terms of the quality perspective, by mining different types of logistics information (e.g. location, temperature level during the in-transit process) collected by RFID technology and cold chain solutions (i.e. temperature sensor in this case), the supply chain quality sustainability assurance process has been significantly enhanced. For example, with the mining results from association rules mining, and with the (mined) results aggregated in probabilities, whereby the most recommended settings are listed in descending order, there is no need for logistics operators to determine the quality assurance settings based on their own experience. Before the implementation of QSDSS, it was inevitable that some of the wine products would be damaged, at least to some extent, owing to wrong decisions on the in-transit wine storage setting. With QSDSS in place, all the operators need to do is to input the logistics information, and then QSDSS will automatically suggest corresponding settings for particular logistics flows. One year after the adoption of QSDSS (i.e. January 2011–December 2011), the present Collazoni study shows an overall 60% decrease in product return rate from customers.

Table 1
First 10 interesting rules generated for Route "A–B".

Rule	Support	Confidence
1. Temperature = 10 °C → Type = Product C	0.67672241	1
2. Season = Summer + Temperature = 7 °C → Type = Product C	0.67672241	1
3. Event Time = 05:00 + Season = Winter → Type = Product B	0.663344482	1
4. Mode = Air-cargo + Event Time = 05:00 → Type = Product A	0.653344482	1
5. Type = Product C + Mode = Air-cargo → Type = Product B	0.5953177	0.9569892
6. Mode = Air-cargo + Season = Winter → Type = Product A	0.583010033	0.9
7. Temperature = 7 °C → Type = Product B	0.5737124	0.8947368
8. Season = Winter + Temperature = 15 °C → Type = Product C	0.57351171	0.8888889
9. Season = Winter → Type = Product A	0.5891639	0.8784314
10. Mode = Sea + Event Time = 00:00 → Type = Product B	0.5547157	0.8732395

Table 2
Normalized weight of unique list of quality assurance settings.

Factor	Route: A–B	Route: B–C	Normalized weight
Temperature = 10 °C	0.78	0.64	0.77
Season = Winter	0.62	0.72	0.65
Mode = air-cargo	0.68	0.66	0.76
Event time = 04:00	0.76	0.74	0.72
…	…	…	…

5.2. *Inspection cost reduction*

Since the implementation of QSDSS in Collazoni, inspection cost is seen to have been reduced in several areas:

- Cost of re-shipping wine products if the product is damaged (for example, because the predefined temperature range is exceeded).
- Cost of transportation of continual shipping of wine products when discovering the products are in poor quality (during the in-transit process).

With the intelligent settings recommendation, the number of quality checks is reduced; the real-time data collected by temperature sensor allows the operator to accurately monitor the wine quality (e.g. whether the temperature is within the predefined range). Overall, in the case of Collazoni, inspection cost has been reduced by 45%, and the number of quality checks has shrunk from twice per month to once per month.

5.3. *Customer satisfaction enhancement and brand name protection*

With an increase of 75% in the quality level of red wine products provided to the customer (i.e. number of bottles of damaged red wine decreased from 2134 in 2010 to 530 in 2011), there is a significant decrease in product returns. The enhancement in red wine quality brought about by the adoption of QSDSS benefits both brand owners and customers, thereby enhancing the company′s corporate image and customers′ confidence in the products they supply. Moreover, by providing the quality assurance settings with weightings, where wines are found to be damaged QSDSS can assist the company in investigating further in terms of scrutinizing which supply chain parties and routes are involved.

5.4. *Supply chain visibility improvement*

QSDSS supports more effective communication among the supply chain participants, enabling visualization of hidden supply chain information. Through the adoption of data mining techniques, operators can analyze the life-cycle transactions of products on a user-friendly interface. All such information is stored in the centralized databases, closing the decision making gaps between supply chain participants.

In summary, the proposed system offers an effective solution to address the supply chain quality sustainability issues. Results of the case study validate the feasibility of adopting the proposed approach. The highly effective real-time quality monitoring and settings recommendation will enhance quality assurance to a significant extent.

6. Conclusion

This paper has proposed a new approach QSDSS, to provide supply chain quality assurance solutions in food supply chains. This infrastructural framework, supported by association rule mining and Dempster′s rule, also involves the development of a decision support system of mining logistics solutions with special features to cope with tough quality assurance requirements in food product activities. The major contribution of the proposed system is to improve supply chain quality sustainability by providing proper logistics solutions plans and continuously data mining the logistics settings to ensure the food product quality during transit. The feature of continual data mining means that potential quality problems are not overlooked, and the same mistakes are not repeated in transporting similar batches of product. A large number of useful association rules concerning environmental parameters and quality within a logistics network can be easily extracted. Compared to the traditional food quality assurance process, this paper also introduces a new ranking measurement for assigning a likelihood ratio for each quality assurance setting extracted from the cases. Table 3 highlights the advantages of adopting the data mining approach in food supply chain management in terms of the practical aspects of food quality assurance.

In the case of food quality assurance, operators are heavily reliant on their own knowledge and experience to derive quality assurance plans and guidelines. Yet despite the importance of quality assurance, it is almost impossible for operators to review and revise the settings in every case; therefore the proposed QSDSS framework is also applicable to other food products (e.g. dairy products), where the item′s conditional information and environmental data can be captured and processed in the learning mechanism (i.e. all the new cases will be fed back to the association rules mining algorithm as a data bank) in order to generate the rules for quality settings in the supply chain network.

Although encouraging results have been achieved, there are a number of aspects that need further investigation. First, adequate

Table 3
Comparison of traditional food quality assurance process and proposed data mining approach.

Criteria	Traditional food quality assurance	Proposed data mining approach – QSDSS
Quality of rules determination for quality assurance	More subjective – determined by individual operator's knowledge and experience or industrial standards/guidelines	Objective and without bias – rule generated by analyzing from large group of logistics flow
Usefulness of rules/guidelines	Too board – may not fit for the case as the industrial standards/guidelines are general for all the cases	More specific – fit for the case as all rules are generated by the historical data
Difficulty of rules generation	Passive – All existing rules/guidelines will be revised and reviewed after certain period of time	Active – The data mining approach make the quality assurance settings updated per day as all the new cases (per day) will be used as the learning feedback in building the data mining model

sample data captured through RFID can ensure the quality of association rules. However, the disadvantage is that it may take a long time to identify the significant association rules by computational methods. Second, quantitative attributions in association rule analysis have sharp boundaries that strictly differentiate the elements near the boundary (Kaya and Alhajj, 2005; Lau et al., 2009). Thus, future work will focus on adopting fuzzy set theory to allow uncertainty and imprecision in the behavior of data mining. Moreover, future work will also focus on testing the QSDSS in other food supply chains. All these undertakings will lay a more comprehensive platform for cold chain managers to use the data mining system as a useful decision support tool in ensuring product quality.

Acknowledgment

This research was supported in part by the Seed Corn Research Fund - CILT(UK) 2013.

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